
MUBENCH: Assessment of Multilingual Capabilities of Large Language Models Across 61 Languages

Wenhan Han^{1*} Yifan Zhang² Zhixun Chen² Binbin Liu² Haobin Lin² Bingni Zhang²

Taifeng Wang² Mykola Pechenizkiy¹ Meng Fang^{3,†} Yin Zheng^{2†}

¹Eindhoven University of Technology ²ByteDance ³University of Liverpool

Abstract

Multilingual large language models (LLMs) are advancing rapidly, with new models frequently claiming support for an increasing number of languages. However, existing evaluation datasets are limited and lack cross-lingual alignment, leaving assessments of multilingual capabilities fragmented in both language and skill coverage. To address this, we introduce MUBENCH, a benchmark covering 61 languages and evaluating a broad range of capabilities. We evaluate several state-of-the-art multilingual LLMs and find notable gaps between claimed and actual language coverage, particularly a persistent performance disparity between English and low-resource languages. Leveraging MuBench’s alignment, we propose Multilingual Consistency (MLC) as a complementary metric to accuracy for analyzing performance bottlenecks and guiding model improvement. Finally, we pretrain a suite of 1.2B-parameter models on English and Chinese with 500B tokens, varying language ratios and parallel data proportions to investigate cross-lingual transfer dynamics. Our dataset will be open at <https://huggingface.co/datasets/aialt/MuBench>

1 Introduction

Recent developments in large language models (LLMs) reflect a clear shift toward broad multilingual support. Both academic and industry models increasingly claim proficiency in dozens, even hundreds, of languages, moving beyond the English-centric paradigm of earlier generative models. For instance, Gemma3 [34] reports support for over 140 languages, while Qwen3 [4] emphasizes wide linguistic coverage across 119 languages and dialects. Proprietary models such as GPT-4o [2], Claude [1, 3], and Gemini [32] also highlight strong multilingual capabilities, though the exact number of supported languages remains undisclosed.

Despite rapid advances in multilingual LLMs, evaluating their capabilities across languages remains a core challenge. Assessments should go beyond per-language task performance to include relative performance across languages, cross-lingual knowledge transfer [18, 11], and robustness in mixed-language contexts [9, 15]. Meaningful evaluation along these dimensions requires broad language and task coverage, as well as aligned test samples across languages. Existing multilingual benchmarks fall short in at least one of these aspects. Some, like CMMLU [20], ArabicMMLU [16], and INCLUDE [29], provide culturally grounded test items in specific languages but lack cross-lingual alignment. Others extend English benchmarks via translation [31, 22, 17, 37], enabling alignment but often with limited language coverage, sample size, or task diversity. For instance, BenchMAX [14] spans 17 languages and 10 tasks but with few samples per language. BMLAMA [25] covers 53 languages but focuses only on factual knowledge, while GeoMLAMA [38] targets commonsense variation in just five languages. In sum, no existing benchmark offers the necessary combination of broad language

*Work done during Wenhan’s internship at ByteDance.

coverage, task diversity, and aligned samples to systematically evaluate multilingual proficiency in LLMs.

To address these limitations, we introduce **MUBENCH**, a comprehensive multilingual benchmark spanning 61 languages and a diverse range of tasks, including natural language understanding, commonsense reasoning, factual recall, knowledge-based QA, academic and technical reasoning, and truthfulness. **MUBENCH** ensures cross-lingual alignment by maintaining consistent test items across languages, enabling fair and direct comparisons. We construct **MUBENCH** by translating widely used English benchmarks through an automated pipeline with rigorous quality control, enforcing semantic consistency and linguistic purity to ensure translations are both faithful and idiomatic. To reflect real-world usage, we include code-switched variants that mix multiple languages within a single test item, allowing evaluation under multilingual input conditions. To characterize content diversity, we apply a two-level domain taxonomy to classify samples by topic and domain. We also perform cultural applicability checks to remove items with obscure cultural references or Western-centric biases, mitigating cultural skew. Finally, stratified human evaluations across 16 languages validate the quality and fidelity of the translations.

Using **MUBENCH**, we conduct extensive evaluations of state-of-the-art LLMs and find that current models often fall short of their claimed multilingual coverage. A persistent performance gap remains between English and low-resource languages, and this gap does not consistently narrow with increased model size. In code-switched settings—where multiple languages appear within a single input—larger models do not necessarily exhibit greater robustness. Leveraging **MUBENCH**'s fully aligned test samples, we analyze cross-lingual consistency and observe stable inter-language correlation patterns in each model, revealing implicit structures in multilingual knowledge sharing. To further examine cross-lingual transfer, we pretrain six 1.2B-parameter models on English and Chinese with varying amounts of parallel data. Results show that parallel corpora improve both accuracy and consistency, particularly when one language dominates in training. These findings highlight the importance of analyzing the relationship between consistency and accuracy as a diagnostic tool for identifying multilingual performance bottlenecks—whether due to insufficient task knowledge or limited generalization across languages. **MUBENCH** thus provides a rigorous framework for understanding and advancing multilingual LLM development.

To summary, this paper makes the following key contributions:

- We introduce **MUBENCH**, a multilingual benchmark supporting 61 languages that enables consistent and cross-lingual evaluation across a variety of tasks, including natural language understanding (NLU), commonsense reasoning, factual recall, knowledge-based QA, academic & technical reasoning, and truthfulness.
- We develop a robust pipeline to ensure the quality of multilingual extensions and validate its effectiveness through human evaluation.
- We conduct extensive experiments to evaluate **MUBENCH**'s utility, providing valuable insights into the strengths and weaknesses of existing multilingual LLMs. Assessment is also conducted on model performance in mixed-language contexts and multi-lingual consistency. In addition, we pretrain several small models to examine the precise impact of parallel data on cross-lingual capability transfer.

2 MUBENCH

We extend widely-used English benchmarks to a broader set of languages while covering a diverse range of capabilities, including: Natural Language Understanding: SNLI [8], MultiNLI [36] and WinoGrande [30]; Commonsense Reasoning: HellaSwag [39] and StoryCloze [23]; Factual Recall: BMLAMA [25]; Knowledge-based QA: MMLU [13] and MMLUPro [35]; Academic & Technical Reasoning: GPQA [28], ARC-Easy and ARC-Challenge [10]; Truthfulness: TruthfulQA [21]. This selection also spans a range of difficulty levels, from relatively simple datasets like StoryCloze to more challenging ones such as GPQA. For language selection, we chose the 61 most widely spoken languages based on the number of native speakers, covering over 60% of the global population (native speakers only) [6]. Figure 1 illustrates the languages, data structure, and examples of **MUBENCH**.

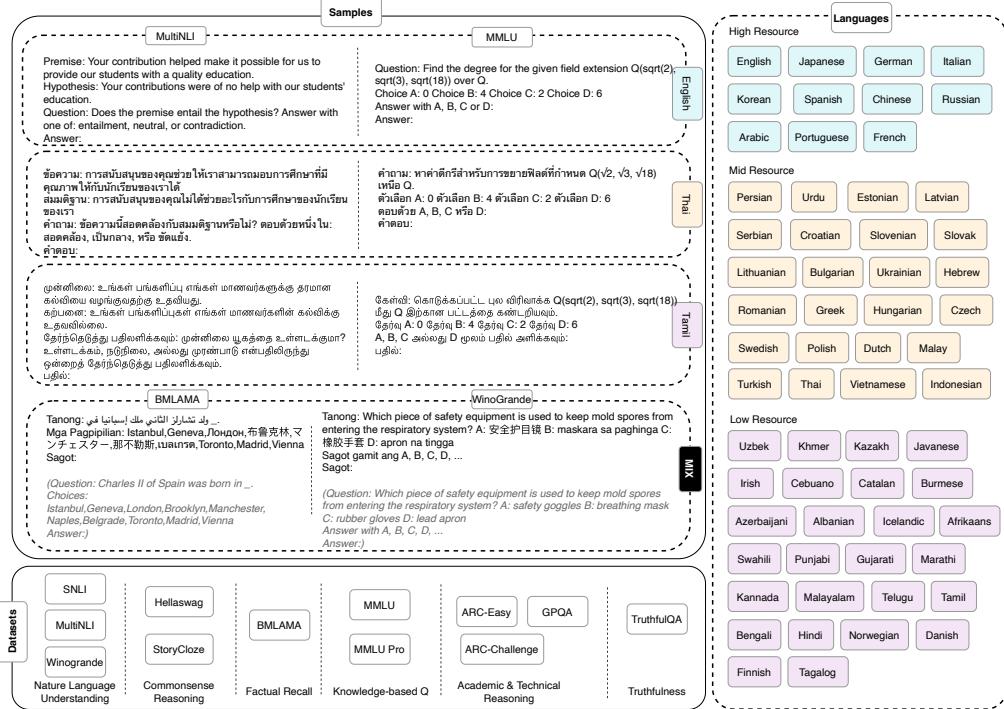


Figure 1: Overview of MuBENCH. MuBENCH supports 61 languages and covers popular datasets for evaluating natural language understanding, knowledge, and reasoning abilities. It also provides multiple variants for each dataset to accommodate different evaluation methods.

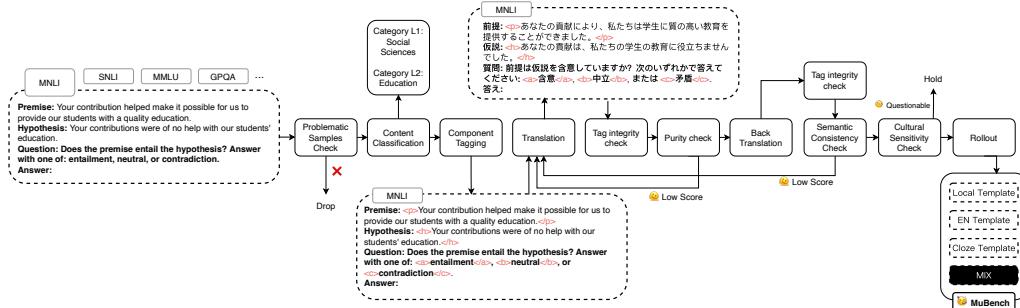


Figure 2: MuBENCH data collection pipeline. MuBENCH has established an automated benchmark translation framework with strict rules to control the quality. Each sample is labeled with content categories and undergoes a cultural sensitivity check.

2.1 Data Pipeline

We developed a rigorous data pipeline, as shown in Figure 2, comprising several main stages: **content classification**, **translation**, **semantic consistency evaluation**, **translation purity assessment**, and **cultural sensitivity check**. The finalized dataset variants constitute MuBENCH.

Content Classification In addition to covering a broad spectrum of capabilities, MuBENCH also emphasizes sample-level diversity analysis. To achieve this, we extend the subject classification schema from MMLU by introducing additional categories that capture more everyday and real-world scenarios, structured in a two-level hierarchy. For each benchmark sample, GPT-4o is used to perform content-based classification—focusing on the topic rather than question type—by first selecting the most suitable high-level category, followed by a corresponding subcategory within it.

Translation To preserve the structural consistency of test samples and enable future flexibility, we wrap each component of a question—such as the prompt and answer choices—with explicit tags and concatenate them into a unified text block for translation via GPT. Post-translation, we perform strict validation to ensure tag integrity; samples with missing or corrupted tags are flagged for retranslation. This design ensures the complete and faithful translation of the prompt, question stem, and answer choices. It also facilitates flexible modification of question formats in the future, allowing adaptation to different evaluation protocols tailored to various model types. Crucially, this design enables the construction of mixed-language test cases, allowing for targeted assessment of LLMs under code-switching and multilingual conditions.

Semantic Consistency Evaluation At this stage, we control for semantic shifts introduced during translation. Each sample is first translated into the target language using GPT-4o, then back-translated into English. The original and back-translated English texts are compared, with GPT-4o assigning a semantic consistency score on a custom 1-to-5 scale. Samples receiving low scores (1 or 2) are flagged for retranslation. This procedure not only ensures semantic fidelity but also serves as a proxy for evaluating GPT-4o’s translation performance in low-resource languages.

Traslation Purity Assessment Maintaining semantic consistency alone is insufficient; translations must also exhibit linguistic authenticity in the target language and avoid inappropriate English intrusions. While the retention of certain English proper nouns may be acceptable, we prioritize replacing them with widely recognized equivalents in the target language to ensure natural and native-like expression. To evaluate this, we define a 1-to-5 scoring rubric and prompt GPT to assess the linguistic purity of each translation.

Cultural Sensitivity Checking Finally, It is essential to ensure that a question, once translated into the target language, remains culturally appropriate and does not conflict with the cultural context of that language. Commonsense knowledge can vary significantly across cultures, potentially altering the correct answer if cultural assumptions shift during translation. To address this, we design a prompt that instructs GPT-4o to identify and annotate instances of cultural shift in the translated samples.

Rollout We construct several variants for each tasks. **Local Template:** Uses the native-language prompt and content to assess the model’s ability to follow instructions and answer within the linguistic context of the target language. **EN Template:** Keeps the sample content in the target language but uses the English prompt. This format aligns with many existing multilingual benchmarks and often leads to improved performance due to models’ stronger instruction-following capabilities in English. **Cloze Template** [7, 10]: Removes explicit task instructions and instead organizes the question and answer choices into natural sentences. Model performance is evaluated based on which option yields the lowest perplexity (PPL). This format is particularly effective for early-stage or smaller models that may struggle with instruction comprehension. **MIX:** For each of the above variants, we additionally construct a code-switched version by randomly replacing components (e.g., prompt, options) with content in another language at a controlled probability, allowing robust testing under mixed-language settings.

2.2 Data Analysis

Statistics Table 1 presents the number of samples included in each dataset within MUBENCH, which constitutes a significantly larger scale than previous dataset expansion efforts. During the final rollout, we removed samples flagged for cultural sensitivity, as well as those receiving the lowest scores in semantic consistency and linguistic purity evaluations. Moreover, all languages are aligned; thus, if a sample is filtered out in one language, its counterparts in all other languages are also removed accordingly. More details of cultural sensitive samples and the diversity are present in the appendix.

Table 1: Sample statistics of MUBENCH. **CS** stands for Culturally Sensitive

Dataset	Origin Samples	SC Samples	Final Samples
SNLI	613,050	5,314	549,000
MultiNLI	602,802	4,091	541,924
StoryCloze	95,221	2,522	81,252
WinoGrande	80,322	220	76,860
BMLAMA	413,831	1,125	369,721
MMLU	873,946	18,058	768,112
MMLU Pro	738,212	5,302	696,315
HellaSwag	615,534	8,331	554,368
ARC-Easy	147,986	72	146,949
ARC-Challenge	74,542	28	74,054
GPQA	27,328	0	27,328
TruthfulQA	49,837	3,149	35,868
Total	4,332,611	48,212	3,921,751

2.3 Quality Control and Human Evaluation

During dataset translation, samples scoring below 3 in either semantic consistency or linguistic purity were retranslated multiple times.

We conducted human evaluations on 2,000 samples per language across 15 languages, using the same scoring criteria. Additionally, 100 matched samples from 9 languages in OpenAI MMMLU² and MUBENCH were evaluated to directly compare GPT-4o translations with human ones.

Table 2 shows that human scores for MUBENCH and OpenAI MMMLU are closely aligned, with no significant difference across 8 of 9 languages; the only exception is Chinese, where MUBENCH shows slightly lower consistency. Table 3 compares GPT-4o’s self-assessments with human scores, revealing that GPT-4o tends to underrate its translations, indicating conservative scoring. Overall, MUBENCH achieves translation quality on par with human-translated benchmarks. The detail of consistency and purity distribution are included in the appendix.

Table 2: Per-language comparison of Semantic Consistency and Translation Purity between OpenAI-MMMLU and MUBENCH-MMMLU (mean scores only, with t -test p -values).

Lang	n	Semantic Consistency			Translation Purity		
		MMMLU	Ours	p	MMMLU	Ours	p
es	100	4.91	5.00	0.0061	4.93	4.98	0.1667
ja	100	4.13	4.24	0.1803	3.73	3.81	0.2188
pt	100	4.84	4.89	0.3718	4.94	4.94	1.0000
ko	100	4.73	4.78	0.5663	4.51	4.45	0.5471
it	100	4.79	4.76	0.7075	4.94	4.97	0.3197
id	100	4.95	4.93	0.5298	4.83	4.88	0.2534
de	100	5.00	4.95	0.1324	5.00	5.00	—
zh	100	4.31	3.85	0.0000	4.69	4.79	0.0584
fr	100	5.00	5.00	—	4.98	4.96	0.4823
All	900	4.74	4.71	0.2980	4.73	4.75	0.3700

Table 3: Per-language GPT vs Human ratings on Semantic Consistency and Translation Purity (mean scores).

Lang	Semantic Consistency		Translation Purity	
	Human	GPT	Human	GPT
th	4.8649	3.8873	4.8054	3.7173
es	4.9467	4.1066	4.9255	3.8264
fr	4.9935	4.1887	4.9034	3.7774
vi	4.8357	3.9561	4.6028	3.8437
tr	4.7813	3.9530	4.6138	3.8236
id	4.8593	4.1733	4.7484	3.6684
tl	4.7384	4.0348	4.6805	3.3640
ko	4.6737	3.9489	4.5687	3.8825
pt	4.7742	4.1251	4.7759	3.9740
nl	4.8050	4.1764	4.7774	3.7391
it	4.7744	4.1889	4.7824	3.7975
ru	4.7290	4.1787	4.7607	3.9749
de	4.8599	4.3550	4.8283	3.7545
zh	4.3580	4.0449	4.7393	3.9308
ja	4.1038	4.1497	3.6227	4.0146

3 Multilingual Capability Evaluation

3.1 Overview

In this section, we conduct a comprehensive evaluation of popular multilingual models from the research community. Since the pretraining stage plays a crucial role in determining the multilingual capabilities of large language models (LLMs), our evaluation focuses on the base versions of various model families. While MUBENCH is designed with the flexibility to adapt test samples to different task formats, we mainly focus on its application to the base models. Importantly, MUBENCH allows for evaluations of chat-oriented models by providing instructions tailored to each language.

We perform zero-shot evaluations on **Qwen3** [4], **Qwen2.5** [26], **Gemma2** [33], and **Gemma3** [34] models ranging from 1–3B, 7–14B, up to 70B. Babel [40] series are also included, which are built upon Qwen2.5 models and aims to cover the top 25 most widely spoken languages. Moreover, dedicated for 13 SouthEast Asian (SEA) languages, Sailor2 [12] series is also Qwen2.5-like models and we include them into the comparison. The evaluation is conducted using MUBENCH **cloze template** variants. An exception is made for **SNLI** and **MultiNLI**, where we adopt the **local template** in a QA-style with 10-shot settings. We report accuracy (ACC) on SNLI, MultiNLI, WinoGrande, and BMLAMA, and char-length normalized accuracy (ACC_NORM) on the other datasets. Additionally, we also evaluated **GPT-4o**. Since it is not a base model, we assessed its performance on each benchmark using **local template** and report Exact Match (EM) scores.

Table 4 summarizes the performance of selected LLMs on MUBENCH, along with their performance gaps relative to English. While GPT-4o substantially outperforms open-source base models across the board (noting that evaluation protocols differ), it still exhibits a clear drop in performance for non-English languages.

²<https://huggingface.co/datasets/openai/MMMLU>

Table 4: Performance of LLMs on MUBENCH. The values in parentheses indicate the score differences relative to English performance.

	MNLI	StoryCloze	WinoGrande	BMLAMA	MMLU	HellaSwag	ARCEasy	ARCChallenge
Proprietary Model								
gpt-4o-2024-05-13	69.78 (-11.18)	97.68 (-1.62)	71.68 (-10.35)	66.87 (-6.90)	70.01 (-2.26)	83.02 (-10.75)	93.64 (-5.00)	87.32 (-7.35)
Model (1–4B)								
Qwen3-0.6B-Base	38.45 (-30.53)	56.05 (-15.78)	50.67 (-6.20)	27.17 (-32.19)	26.88 (-5.38)	31.01 (-21.29)	29.75 (-19.25)	24.62 (-8.89)
Qwen3-1.7B-Base	56.33 (-24.75)	59.71 (-17.84)	50.99 (-6.30)	31.89 (-28.45)	28.13 (-7.30)	35.68 (-28.29)	33.46 (-23.00)	26.88 (-9.80)
Qwen3-4B-Base	69.26 (-4.47)	64.16 (-17.19)	53.27 (-10.04)	37.82 (-26.87)	30.18 (-8.38)	42.52 (-29.57)	37.55 (-19.51)	30.09 (-9.43)
Qwen2.5-0.5B	35.10 (-25.94)	54.26 (-17.10)	50.39 (-3.44)	26.42 (-39.55)	26.27 (-4.85)	29.42 (-20.54)	28.06 (-21.83)	23.67 (-7.34)
Sailor2-1B	34.56 (+2.06)	54.82 (-18.32)	49.98 (-5.80)	28.37 (-37.95)	26.22 (-3.45)	29.88 (-20.30)	28.83 (-18.18)	23.51 (-5.79)
Qwen2.5-1.5B	46.11 (-29.98)	56.17 (-24.63)	50.48 (-10.94)	31.91 (-37.04)	27.19 (-7.73)	31.64 (-33.95)	29.51 (-24.67)	24.62 (-12.92)
gemma-3-1b-pt	32.66 (+0.22)	56.91 (-10.74)	51.62 (-5.76)	41.71 (-27.31)	26.62 (-1.29)	31.11 (-13.02)	28.94 (-7.77)	24.84 (-2.05)
gemma-3-4b-pt	42.48 (-5.82)	58.31 (-9.65)	56.01 (-11.43)	52.57 (-17.96)	26.70 (-1.40)	34.31 (-16.81)	29.26 (-10.08)	24.47 (-2.94)
gemma-2-2b	34.51 (-12.74)	63.98 (-18.91)	52.53 (-11.94)	40.48 (-30.73)	28.05 (-6.27)	40.29 (-30.46)	33.45 (-16.53)	27.36 (-8.81)
Model (7–20B)								
Qwen3-8B-Base	76.16 (-6.56)	67.87 (-16.42)	55.41 (-12.03)	47.44 (-24.70)	31.47 (-8.14)	47.72 (-28.02)	40.51 (-17.90)	31.73 (-8.13)
Qwen3-14B-Base	81.63 (-0.92)	71.14 (-13.61)	57.67 (-15.04)	51.72 (-21.14)	32.61 (-8.22)	52.86 (-25.90)	42.75 (-15.41)	33.71 (-5.98)
Qwen2.5-7B	67.23 (-18.14)	61.88 (-22.02)	51.68 (-14.68)	36.02 (-28.39)	29.77 (-9.56)	39.52 (-36.92)	35.49 (-24.49)	28.14 (-11.98)
Sailor2-8B	54.66 (-25.99)	61.89 (-20.62)	52.59 (-11.96)	40.26 (-30.47)	28.25 (-7.76)	38.44 (-34.76)	34.11 (-22.44)	26.62 (-11.01)
Babel-9B	66.38 (-22.27)	61.96 (-21.48)	53.29 (-14.72)	42.73 (-29.34)	29.15 (-9.30)	40.57 (-34.25)	34.25 (-27.73)	27.64 (-13.08)
Qwen2.5-14B	74.24 (-11.83)	66.50 (-19.26)	50.19 (-11.89)	23.68 (-31.04)	31.64 (-9.70)	45.62 (-35.09)	39.05 (-20.59)	31.20 (-11.07)
Sailor2-20B	73.36 (-16.07)	67.41 (-18.50)	56.30 (-18.64)	48.11 (-25.13)	30.61 (-8.94)	46.74 (-32.83)	38.14 (-20.95)	30.36 (-10.71)
gemma-3-12b-pt	37.08 (-4.45)	55.42 (-4.02)	61.40 (-11.56)	59.61 (-12.17)	26.27 (-0.87)	30.50 (-4.01)	28.27 (-3.40)	24.23 (+1.21)
gemma-2-9b	65.10 (-12.05)	73.40 (-12.28)	57.98 (-13.83)	53.59 (-18.12)	31.64 (-7.18)	55.66 (-22.19)	41.75 (-13.91)	33.27 (-7.11)
Model (>20B)								
Qwen2.5-32B	80.36 (-7.61)	68.19 (-18.57)	56.95 (-17.91)	48.84 (-23.45)	33.30 (-8.51)	49.43 (-32.07)	41.51 (-17.96)	33.12 (-10.95)
Qwen2.5-72B	84.48 (-5.53)	71.89 (-15.42)	59.17 (-18.82)	52.87 (-19.79)	36.25 (-7.59)	54.99 (-28.77)	46.73 (-15.50)	36.40 (-9.13)
Babel-83B	85.29 (-5.04)	71.40 (-15.83)	58.52 (-18.89)	52.46 (-20.91)	34.75 (-8.19)	54.65 (-28.33)	43.08 (-18.51)	34.47 (-8.06)
gemma-3-27b-pt	77.12 (-8.60)	79.06 (-8.48)	63.49 (-13.34)	61.74 (-10.48)	36.46 (-4.84)	66.09 (-14.28)	48.18 (-7.01)	37.99 (-3.59)
gemma-2-27b	75.38 (-8.58)	77.21 (-10.17)	60.78 (-15.81)	56.09 (-14.85)	34.09 (-6.76)	62.08 (-20.02)	44.23 (-9.48)	35.70 (-3.90)

Among open models, Qwen demonstrates strong and consistent performance across a wide range of tasks. This is particularly evident in inference-focused benchmarks (MultiNLI), knowledge-intensive tasks (BMLAMA, MMLU), and QA-style datasets (ARC). Both Qwen3-14B and Qwen2.5-72B stand out for their balanced and robust performance across nearly all evaluation metrics. In contrast, Gemma models—especially Gemma-3-27B-pt—excel in narrative and commonsense reasoning tasks such as StoryCloze and HellaSwag, and perform competitively on factual knowledge benchmarks like BMLAMA. Overall, Qwen models offer stronger and more stable performance, whereas Gemma exhibits sharper peaks in specific reasoning-heavy tasks. Both Babel-9B and Sailor2-8B are extended from Qwen2.5-7B. Babel-9B generally retains the capabilities of its base model, with modest gains in factual QA and language understanding tasks (e.g., BMLAMA, WinoGrande). In contrast, Sailor2-8B shows a broad regression, suggesting that its specialized training on Southeast Asian languages may have compromised its performance on other languages. Notably, Babel-83B underperforms relative to its baseline Qwen2.5-72B, despite a larger parameter count, with performance degradation particularly evident on knowledge-heavy tasks such as MMLU and ARC.

As expected, larger models tend to achieve better overall performance. However, the relative performance gap between English and other languages does not consistently narrow with scale. This trend holds across most tasks, with the exception of SNLI. These findings suggest that the performance gap for low-resource languages remains persistent, and only begins to close when a model approaches saturation in English performance on a given benchmark. The evaluation results on full MUBENCH test sets are presented in Appendix C.

3.2 Per-Language Performance Comparison

Figure 3 presents the per-language performance of the evaluated LLMs, measured as the mean score across all datasets for each language. As expected, models tend to perform better on high-resource languages such as English, Chinese, and Spanish, while lower-resource languages generally yield lower scores. GPT-4o demonstrates strong multilingual performance across all 61 languages. However, when normalized against its own English performance, notable drops are observed in languages such as Tagalog (tl) and Burmese (my). Interestingly, several affected languages—such as Chinese (zh) and German (de)—are not traditionally considered low-resource, underscoring the broader challenges in achieving consistent performance across typologically and culturally diverse languages.

Among open-source models, Gemma-3-27B emerges as the best overall performer, achieving consistently strong results across nearly all languages. The Babel and Sailor2 models demonstrate notable gains in their targeted language groups, though often at the expense of reduced performance in others.

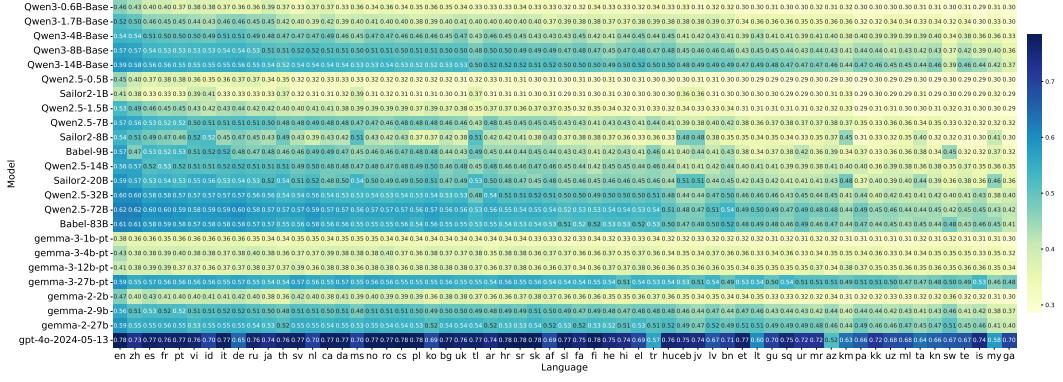


Figure 3: Model performance by language.

Larger models from the Qwen2.5 and Qwen3 series also perform well, with performance improving steadily with increased model size. These findings highlight the critical role of both scale and model design in achieving robust and balanced multilingual capabilities.

3.3 Cross-Lingual Consistency Evaluation

Evaluating multilingual LLMs goes beyond per-language accuracy. Consistency across languages—producing similar responses even when incorrect—signals shared cross-lingual representations and potential for improvement. As such, consistency serves as a crucial complement to accuracy.

Qi et al. [25] introduced BMLAMA

to evaluate cross-lingual consistency using ranking-based scores. However, for multiple-choice questions with discrete answers (e.g., “What is the capital of China?”), only the top choice matters—ranking secondary options is often irrelevant and may distort consistency assessment. We instead use a multilingual consistency (MLC) metric based on exact Top-1 answer match across languages: $\text{MLC}(l, l') = \frac{1}{|N|} \sum_{i=1}^N \mathbf{1}_{c_i=c'_i}$, where N is the number of questions, l and l' are two languages, and c_i, c'_i are the model’s Top-1 choices for the same question in l and l' , respectively. All MUBENCH samples are aligned across 61 languages, providing a robust foundation for consistent cross-lingual evaluation and analysis of knowledge transfer.

Table 5 reports average MLC scores across all language pairs, and between each language and English. In general, MLC correlates with accuracy—models with higher accuracy tend to exhibit better consistency. However, notable exceptions reveal important dynamics. For example, in MultiNLI, GPT-4o achieves lower accuracy than several open-source models above 20B parameters, yet maintains competitive or superior consistency (e.g., outperforming gemma-2-27b), suggesting stronger cross-lingual representation alignment.

Conversely, in MMLUPro and GPQA, GPT-4o significantly outperforms gemma-3-27b-pt and gemma-2-27b in accuracy, but lags in consistency, indicating less overlap in correct answers across languages. These discrepancies highlight that accuracy and consistency reflect distinct facets of

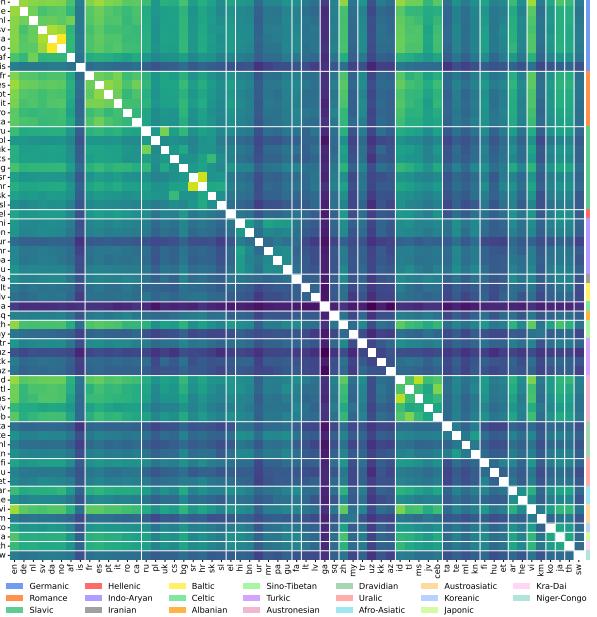


Figure 4: Consistency of Qwen3-14B-Base across languages tested on BMLAMA.

multilingual performance. Low consistency suggests fragmented cross-lingual representations, while low accuracy indicates limited task knowledge. We therefore advocate using MLC alongside accuracy to better diagnose model weaknesses and inform multilingual model development. Additionally, we find that consistency between each language and English is generally higher than the average across all language pairs, reaffirming English’s central role in cross-lingual generalization.

Table 5: Consistency across languages. ‘All’ refers to the average consistency across all language pairs, while ‘vs. EN’ indicates the average consistency between each language and English.

	MNLI		BMLAMA		MMLU		MMLUPro		GPQA		ARCEasy		ARCChallenge	
	all	vs. EN	all	vs. EN	all	vs. EN	all	vs. EN	all	vs. EN	all	vs. EN	all	vs. EN
Proprietary Model														
gpt-4o-2024-05-13	74.60	79.25	66.21	74.67	68.42	69.71	42.46	47.07	47.46	43.93	90.34	94.28	84.52	89.24
Model (1-4B)														
Qwen3-0.6B-Base	49.51	51.04	29.64	35.36	49.22	48.98	44.84	42.07	64.00	63.52	39.42	40.44	40.94	41.26
Qwen3-1.7B-Base	56.72	62.92	33.92	42.06	49.82	50.21	44.14	42.48	64.00	64.70	41.45	43.91	42.66	43.48
Qwen3-4B-Base	70.39	70.99	36.24	44.74	51.08	52.36	44.42	43.41	64.16	65.36	43.54	46.92	44.13	45.65
Qwen2.5-0.5B	42.98	48.39	27.93	34.21	47.67	45.94	45.06	40.15	62.83	60.68	37.17	37.19	39.40	38.03
Sailor-1B	58.48	71.72	28.96	36.57	48.64	48.28	46.54	43.36	63.88	62.98	38.56	39.51	40.45	40.46
Qwen2.5-1.5B	45.29	55.07	32.64	40.60	48.31	47.52	43.53	39.96	63.44	61.53	38.52	39.92	39.87	38.64
gemma-3-1b-pt	86.21	92.58	40.64	51.17	52.79	54.52	48.13	48.67	65.85	67.30	40.81	43.46	42.78	43.76
gemma-3-4b-pt	42.04	44.77	51.35	61.04	50.89	53.02	45.52	45.80	64.08	64.18	39.47	42.46	41.23	42.81
gemma-2-2b	41.50	29.26	39.24	49.81	53.82	54.36	48.60	47.53	67.84	68.35	43.21	46.23	44.09	45.98
Model (7-20B)														
Qwen3-8B-Base	74.47	78.24	45.48	55.63	51.39	52.52	44.59	43.79	64.79	66.12	45.23	48.91	45.21	46.85
Qwen3-14B-Base	80.76	79.75	49.80	59.66	52.59	54.06	45.02	44.74	64.85	66.84	46.26	49.78	46.01	48.45
Qwen2.5-7B	65.37	74.53	34.49	42.58	49.28	50.29	42.92	42.04	61.89	62.62	41.29	45.31	41.33	43.29
Sailor-8B	49.86	60.37	38.36	48.17	50.40	50.93	44.98	43.13	64.89	64.63	42.04	44.87	42.07	43.57
Babel-9B	58.75	69.49	40.97	51.46	46.99	49.04	40.81	40.83	61.82	63.79	39.53	44.21	39.66	42.06
Qwen2.5-14B	74.97	79.11	26.19	31.21	50.08	51.71	43.35	42.79	62.96	64.29	43.20	47.79	42.89	45.41
Sailor-20B	73.25	78.18	46.03	56.05	50.96	51.85	45.07	44.40	65.84	68.21	44.16	47.80	44.43	46.68
gemma-3-12b-pt	47.53	59.61	58.73	66.71	48.36	50.23	42.68	43.66	60.44	60.74	36.69	39.52	38.79	39.74
gemma-2-9b	70.00	74.91	51.62	61.12	55.87	57.51	50.12	49.77	71.00	73.30	47.12	51.71	47.02	49.58
Model (>20B)														
Qwen2.5-32B	80.83	84.48	46.54	56.12	50.91	52.75	43.07	43.12	61.88	63.80	44.21	48.69	43.74	47.11
Qwen2.5-72B	84.65	88.06	50.23	59.90	53.01	55.39	45.08	45.26	64.67	66.63	47.44	52.25	45.83	49.05
Babel-83B	85.20	88.34	50.17	59.73	52.70	55.09	45.46	45.64	65.66	66.39	46.24	50.90	45.59	48.59
gemma-3-27b-pt	77.43	82.09	61.02	68.10	58.66	61.91	53.24	54.88	73.72	74.46	52.16	55.87	51.07	54.29
gemma-2-27b	74.24	77.78	53.65	62.81	55.39	58.03	47.98	48.62	66.33	68.82	48.27	51.44	48.06	51.77

Beyond measuring overall consistency, MLC scores also reveal patterns of cross-lingual interaction within LLMs. Figure 4 visualizes these interactions on the BMLAMA task, with 61 languages grouped by family and ordered by resource availability. Each cell represents the consistency score between a language pair. Since consistency is influenced by accuracy, to isolate language interaction patterns independent of accuracy, we normalize MLC scores by the average accuracy of each pair:

$$\text{Rel-MLC}(l, l') = \frac{\text{MLC}(l, l')}{\text{Mean}(\text{ACC}_l, \text{ACC}_{l'})}.$$

We observe similar patterns across different models.

Despite differences in performance across models, relative MLC patterns remain stable. Strong intra-family consistency is evident, especially within Germanic, Romance, Slavic, Indo-Aryan, Austronesian, and Dravidian families. Some pairs, like Croatian (hr) and Serbian (sr), show exceptionally high alignment. Notably, cross-family consistency—especially involving English and other Indo-European languages—extends to most language families, including isolates.

These stable patterns likely reflect the underlying distribution of multilingual training data, rather than specific model architectures. Understanding such inter-language dynamics is essential for improving multilingual balance in LLMs.

3.4 Performance under Code-Switched Contexts

An often overlooked aspect of multilingual LLMs is their ability to process and remain stable in mixed-language contexts. Chua et al. [9] identified a cross-lingual knowledge barrier in large models. Leveraging MUBENCH, we examine LLM behavior under such scenarios across a wide range of tasks by randomly replacing the template, question stem, and answer choices of each English test sample with other languages at a 0.5 probability. BMLAMA samples may contain up to 9 languages, while other benchmarks include up to 3 per sample.

Figure 5 shows the performance gap between the mixed-language setting and the average score across individual languages. The Qwen series exhibits greater stability in code-switched contexts compared to the gemma models. Interestingly, smaller models often benefit from the presence of English in mixed-language inputs, resulting in higher scores relative to their monolingual average. However, as model size increases, the gap between mixed-language performance and single-language gains

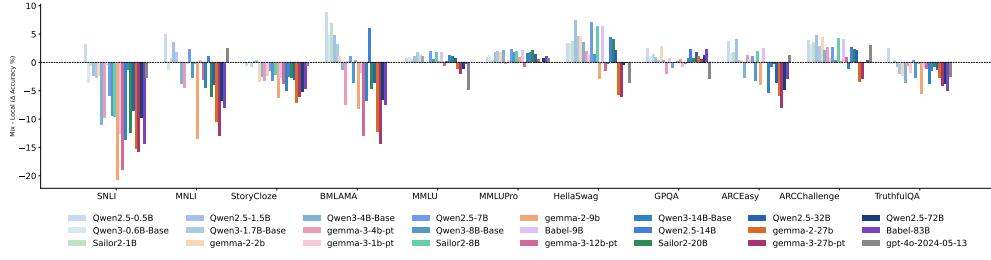


Figure 5: Model performance under mixed-language context.

widens—suggesting that improvements in multilingual understanding do not necessarily translate to better handling of mixed inputs.

These findings highlight the need to treat mixed-language performance as a distinct evaluation target. While LLMs may improve across individual languages, their ability to generalize under code-switching remains limited.

4 Parallel Corpora Impact Study

Consistency and accuracy together provide a holistic view of a model’s multilingual capabilities, revealing both performance and the extent of cross-lingual transfer. Enhancing such transfer remains a key open challenge. While parallel corpora are commonly used to improve cross-lingual generalization, their exact contribution is not well understood. To explore this, we conduct experiments examining how incorporating parallel data under different language ratio settings affects model performance across languages.

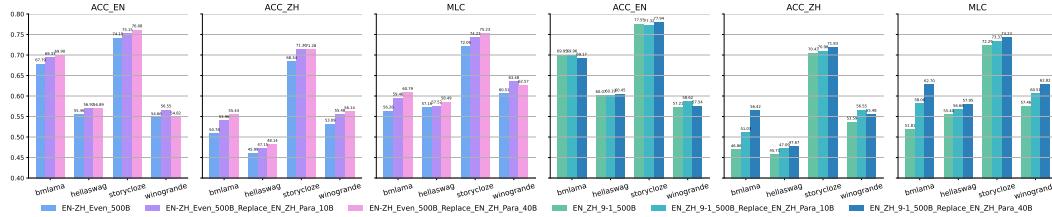


Figure 6: Impact of parallel corpus proportion on language proficiency.

Experimental Setup We pretrain 1.2B-parameter LLaMA-2 models on Chinese and English corpora—two linguistically distant, high-resource languages—cleaned from CommonCrawl. Training is done under two data distributions: (1) equal Chinese-English, and (2) a 1:9 Chinese-to-English ratio, with total tokens fixed at 500B. To assess the impact of parallel data, we translate English into Chinese and filter with COMET [27], keeping only pairs with scores above 0.8, yielding 10B and 40B tokens of parallel data. In each setting, we replace 10B or 40B monolingual tokens—removing equal parts from both languages—to maintain the total token count.

Result Figure 6 shows the performance of six 1.2B-parameter models on natural language understanding and factual knowledge tasks. Even under equal data distribution, English consistently outperforms Chinese, reflecting its dominance in global data availability. Introducing parallel corpora improves overall performance across both data settings, with gains primarily observed in Chinese. This, along with increased consistency, suggests that some English capabilities are effectively transferred to Chinese. Conversely, modest improvements in English performance under the equal distribution setting indicate reciprocal benefits from Chinese. Since both languages are limited to 250B tokens, excessive parallel data—despite its transfer benefits—can reduce overall information diversity due to redundancy. This is evident as the performance gain from 40B tokens of parallel data is marginal compared to 10B. In the 90% English setting, however, even a small amount of parallel data significantly boosts Chinese performance, matching that of a model trained on 250B Chinese tokens. Yet, diminishing returns and even regression (e.g., on WinoGrande) with 40B tokens highlight potential drawbacks of overusing parallel data. These results reveal a trade-off between preserving

information diversity and enhancing cross-lingual transfer, shaped by data ratios and parallel corpus size. They also showcase MUBENCH’s value in probing multilingual dynamics and guiding future LLM development.

5 Conclusion

We present MUBENCH, a comprehensive multilingual benchmark for evaluating large language models (LLMs) across 61 languages. Through rigorous translation quality control and cross-lingual consistency evaluation, MUBENCH provides valuable insights into the strengths and limitations of current multilingual models. Our experiments highlight performance gaps between high-resource and low-resource languages, emphasizing the challenges in achieving consistent cross-lingual capabilities. This work offers a standardized tool for assessing multilingual LLMs and guides future improvements, particularly for low-resource languages.

References

- [1] Claude 3.7 Sonnet and Claude Code \ Anthropic. <https://www.anthropic.com/news/clause-3-7-sonnet>.
- [2] Hello GPT-4o. <https://openai.com/index/hello-gpt-4o/>.
- [3] Multilingual support. <https://docs.anthropic.com/en/docs/build-with-claude/multilingual-support>.
- [4] Qwen3: Think Deeper, Act Faster | Qwen. <https://qwenlm.github.io/blog/qwen3/>.
- [5] SlimPajama: A 627B token, cleaned and deduplicated version of RedPajam. <https://www.cerebras.ai/blog/slimpajama-a-627b-token-cleaned-and-deduplicated-version-of-redpajama>.
- [6] List of languages by number of native speakers. *Wikipedia*, April 2025.
- [7] Norah Alzahrani, Hisham Alyahya, Yazeed Alnumay, Sultan AlRashed, Shaykhah Alsubaie, Yousef Almushayqih, Faisal Mirza, Nouf Alotaibi, Nora Al-Twairesh, Areeb Alowisheq, M Saiful Bari, and Haidar Khan. When Benchmarks are Targets: Revealing the Sensitivity of Large Language Model Leaderboards. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 13787–13805, Bangkok, Thailand, August 2024. Association for Computational Linguistics.
- [8] Samuel R. Bowman, Gabor Angeli, Christopher Potts, and Christopher D. Manning. A large annotated corpus for learning natural language inference. In Lluís Màrquez, Chris Callison-Burch, and Jian Su, editors, *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 632–642, Lisbon, Portugal, September 2015. Association for Computational Linguistics.
- [9] Lynn Chua, Badih Ghazi, Yangsibo Huang, Pritish Kamath, Ravi Kumar, Pasin Manurangsi, Amer Sinha, Chulin Xie, and Chiyuan Zhang. Crosslingual Capabilities and Knowledge Barriers in Multilingual Large Language Models, March 2025.
- [10] Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have Solved Question Answering? Try ARC, the AI2 Reasoning Challenge, March 2018.
- [11] Alexis Conneau, Shijie Wu, Haoran Li, Luke Zettlemoyer, and Veselin Stoyanov. Emerging Cross-lingual Structure in Pretrained Language Models. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 6022–6034, Online, July 2020. Association for Computational Linguistics.

- [12] Longxu Dou, Qian Liu, Fan Zhou, Changyu Chen, Zili Wang, Ziqi Jin, Zichen Liu, Tongyao Zhu, Cunxiao Du, Penghui Yang, Haonan Wang, Jiaheng Liu, Yongchi Zhao, Xiachong Feng, Xin Mao, Man Tsung Yeung, Kunat Pipatanakul, Fajri Koto, Min Si Thu, Hynek Kydlíček, Zeyi Liu, Qunshu Lin, Sittipong Sripaisarnmongkol, Kridtaphad Sae-Khow, Nirattisai Thongchim, Taechawat Konkaew, Narong Borijindargoorn, Anh Dao, Matichon Maneegard, Phakphum Artkaew, Zheng-Xin Yong, Quan Nguyen, Wannaphong Phatthiyaphaibun, Hoang H. Tran, Mike Zhang, Shiqi Chen, Tianyu Pang, Chao Du, Xinyi Wan, Wei Lu, and Min Lin. Sailor2: Sailing in South-East Asia with Inclusive Multilingual LLMs, February 2025.
- [13] Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring Massive Multitask Language Understanding, January 2021.
- [14] Xu Huang, Wenhao Zhu, Hanxu Hu, Conghui He, Lei Li, Shujian Huang, and Fei Yuan. BenchMAX: A Comprehensive Multilingual Evaluation Suite for Large Language Models, February 2025.
- [15] Muhammad Huzaifah, Weihua Zheng, Nattapol Chanpaisit, and Kui Wu. Evaluating Code-Switching Translation with Large Language Models. In Nicoletta Calzolari, Min-Yen Kan, Veronique Hoste, Alessandro Lenci, Sakriani Sakti, and Nianwen Xue, editors, *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, pages 6381–6394, Torino, Italia, May 2024. ELRA and ICCL.
- [16] Fajri Koto, Haonan Li, Sara Shatnawi, Jad Doughman, Abdelrahman Sadallah, Aisha Alraeesi, Khalid Almubarak, Zaid Alyafeai, Neha Sengupta, Shady Shehata, Nizar Habash, Preslav Nakov, and Timothy Baldwin. ArabicMMLU: Assessing Massive Multitask Language Understanding in Arabic. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Findings of the Association for Computational Linguistics: ACL 2024*, pages 5622–5640, Bangkok, Thailand, August 2024. Association for Computational Linguistics.
- [17] Viet Lai, Chien Nguyen, Nghia Ngo, Thuat Nguyen, Franck Dernoncourt, Ryan Rossi, and Thien Nguyen. Okapi: Instruction-tuned Large Language Models in Multiple Languages with Reinforcement Learning from Human Feedback. In Yansong Feng and Els Lefever, editors, *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 318–327, Singapore, December 2023. Association for Computational Linguistics.
- [18] Guillaume Lample and Alexis Conneau. Cross-lingual Language Model Pretraining, January 2019.
- [19] Hector Levesque, Ernest Davis, and Leora Morgenstern. The Winograd Schema Challenge.
- [20] Haonan Li, Yixuan Zhang, Fajri Koto, Yifei Yang, Hai Zhao, Yeyun Gong, Nan Duan, and Timothy Baldwin. CMMLU: Measuring massive multitask language understanding in Chinese, January 2024.
- [21] Stephanie Lin, Jacob Hilton, and Owain Evans. TruthfulQA: Measuring How Models Mimic Human Falsehoods, May 2022.
- [22] Xi Victoria Lin, Todor Mihaylov, Mikel Artetxe, Tianlu Wang, Shuhui Chen, Daniel Simig, Myle Ott, Naman Goyal, Shruti Bhosale, Jingfei Du, Ramakanth Pasunuru, Sam Shleifer, Punit Singh Koura, Vishrav Chaudhary, Brian O’Horo, Jeff Wang, Luke Zettlemoyer, Zornitsa Kozareva, Mona Diab, Veselin Stoyanov, and Xian Li. Few-shot Learning with Multilingual Language Models, November 2022.
- [23] Nasrin Mostafazadeh, Nathanael Chambers, Xiaodong He, Devi Parikh, Dhruv Batra, Lucy Vanderwende, Pushmeet Kohli, and James Allen. A Corpus and Evaluation Framework for Deeper Understanding of Commonsense Stories, April 2016.
- [24] Guilherme Penedo, Hynek Kydlíček, Loubna Ben allal, Anton Lozhkov, Margaret Mitchell, Colin Raffel, Leandro Von Werra, and Thomas Wolf. The FineWeb Datasets: Decanting the Web for the Finest Text Data at Scale, October 2024.

- [25] Jirui Qi, Raquel Fernández, and Arianna Bisazza. Cross-Lingual Consistency of Factual Knowledge in Multilingual Language Models. In Houda Bouamor, Juan Pino, and Kalika Bali, editors, *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 10650–10666, Singapore, December 2023. Association for Computational Linguistics.
- [26] Qwen, An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li, Tianyi Tang, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. Qwen2.5 Technical Report, January 2025.
- [27] Ricardo Rei, Craig Stewart, Ana C. Farinha, and Alon Lavie. COMET: A Neural Framework for MT Evaluation, October 2020.
- [28] David Rein, Betty Li Hou, Asa Cooper Stickland, Jackson Petty, Richard Yuanzhe Pang, Julien Dirani, Julian Michael, and Samuel R. Bowman. GPQA: A Graduate-Level Google-Proof Q&A Benchmark. <https://arxiv.org/abs/2311.12022v1>, November 2023.
- [29] Angelika Romanou, Negar Foroutan, Anna Sotnikova, Zeming Chen, Sree Harsha Nelaturu, Shivalika Singh, Rishabh Maheshwary, Micol Altomare, Mohamed A. Haggag, Sneha A, Alfonso Amayuelas, Azril Hafizi Amirudin, Viraat Aryabumi, Danylo Boiko, Michael Chang, Jenny Chim, Gal Cohen, Aditya Kumar Dalmia, Abraham Diress, Sharad Duwal, Daniil Dzenhaliou, Daniel Fernando Erazo Florez, Fabian Farestam, Joseph Marvin Imperial, Shayekh Bin Islam, Perttu Isotalo, Maral Jabbarishiviari, Börje F. Karlsson, Eldar Khalilov, Christopher Klamm, Fajri Koto, Dominik Krzeminski, Gabriel Adriano de Melo, Syrielle Montariol, Yiyang Nan, Joel Niklaus, Jekaterina Novikova, Johan Samir Obando Ceron, Debjit Paul, Esther Ploeger, Jebish Purbey, Swati Rajwal, Selvan Sunitha Ravi, Sara Rydell, Roshan Santhosh, Drishti Sharma, Marjana Prifti Skenduli, Arshia Soltani Moakhar, Bardia Soltani Moakhar, Ran Tamir, Ayush Kumar Tarun, Azmine Toushik Wasi, Thenuka Ovin Weerasinghe, Serhan Yilmaz, Mike Zhang, Imanol Schlag, Marzieh Fadaee, Sara Hooker, and Antoine Bosselut. INCLUDE: Evaluating Multilingual Language Understanding with Regional Knowledge, November 2024.
- [30] Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. WinoGrande: An Adversarial Winograd Schema Challenge at Scale. <https://arxiv.org/abs/1907.10641v2>, July 2019.
- [31] Shivalika Singh, Angelika Romanou, Clémentine Fourrier, David I. Adelani, Jian Gang Ngui, Daniel Vila-Suero, Peerat Limkonchotiwat, Kelly Marchisio, Wei Qi Leong, Yosephine Susanto, Raymond Ng, Shayne Longpre, Wei-Yin Ko, Sebastian Ruder, Madeline Smith, Antoine Bosselut, Alice Oh, Andre F. T. Martins, Leshem Choshen, Daphne Ippolito, Enzo Ferrante, Marzieh Fadaee, Beyza Ermis, and Sara Hooker. Global MMLU: Understanding and Addressing Cultural and Linguistic Biases in Multilingual Evaluation, February 2025.
- [32] Gemini Team. Gemini: A Family of Highly Capable Multimodal Models, June 2024.
- [33] Gemma Team. Gemma 2: Improving Open Language Models at a Practical Size, July 2024.
- [34] Gemma Team. Gemma 3 Technical Report, March 2025.
- [35] Yubo Wang, Xueguang Ma, Ge Zhang, Yuansheng Ni, Abhranil Chandra, Shiguang Guo, Weiming Ren, Aaran Arulraj, Xuan He, Ziyan Jiang, Tianle Li, Max Ku, Kai Wang, Alex Zhuang, Rongqi Fan, Xiang Yue, and Wenhua Chen. MMLU-Pro: A More Robust and Challenging Multi-Task Language Understanding Benchmark, November 2024.
- [36] Adina Williams, Nikita Nangia, and Samuel Bowman. A Broad-Coverage Challenge Corpus for Sentence Understanding through Inference. In Marilyn Walker, Heng Ji, and Amanda Stent, editors, *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1112–1122, New Orleans, Louisiana, June 2018. Association for Computational Linguistics.

- [37] Weihao Xuan, Rui Yang, Heli Qi, Qingcheng Zeng, Yunze Xiao, Yun Xing, Junjue Wang, Huitao Li, Xin Li, Kunyu Yu, Nan Liu, Qingyu Chen, Douglas Teodoro, Edison Marrese-Taylor, Shijian Lu, Yusuke Iwasawa, Yutaka Matsuo, and Irene Li. MMLU-ProX: A Multilingual Benchmark for Advanced Large Language Model Evaluation, March 2025.
- [38] Da Yin, Hritik Bansal, Masoud Monajatipoor, Liunian Harold Li, and Kai-Wei Chang. GeoM-LAMA: Geo-Diverse Commonsense Probing on Multilingual Pre-Trained Language Models. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang, editors, *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 2039–2055, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics.
- [39] Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. HellaSwag: Can a Machine Really Finish Your Sentence? In Anna Korhonen, David Traum, and Lluís Màrquez, editors, *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4791–4800, Florence, Italy, July 2019. Association for Computational Linguistics.
- [40] Yiran Zhao, Chaoqun Liu, Yue Deng, Jiahao Ying, Mahani Aljunied, Zhaodonghui Li, Lidong Bing, Hou Pong Chan, Yu Rong, Deli Zhao, and Wenzuan Zhang. Babel: Open Multilingual Large Language Models Serving Over 90% of Global Speakers, March 2025.

A Details of MUBENCH

A.1 Language Support

Table 6 presents the languages supported by MUBENCH. We rank the languages by their estimated number of native speakers, using data from Wikipedia³ and other reputable online sources. To estimate the distribution of each language in web-scale data, we also report the number of tokens per language in the Common Crawl corpus. For this, we randomly selected one snapshot from each year between 2022 and 2024 and computed the average token proportion for each language. Considering only native speakers, these languages cover over 60% of the global population. When including second-language speakers, the coverage exceeds 99% worldwide.

Table 6: Languages sorted by native speakers and ratios in Common Crawl (top-down, left-right)

Code	Name	Speakers	Tokens	Code	Name	Speakers	Tokens	Code	Name	Speakers	Tokens
zh	Chinese	1390M	6.34%	ta	Tamil	79M	0.09%	pa	Punjabi	32M	0.01%
es	Spanish	484M	4.14%	ur	Urdu	78M	0.04%	tl	Tagalog	28M	0.02%
ar	Arabic	411M	0.78%	de	German	76M	5.21%	uz	Uzbek	27M	0.01%
en	English	390M	42.62%	id	Indonesian	75M	1.05%	ro	Romanian	24M	0.64%
hi	Hindi	345M	0.31%	fr	French	74M	4.10%	az	Azerbaijani	24M	0.10%
bn	Bengali	242M	0.18%	ko	Korean	81M	0.84%	nl	Dutch	23M	1.57%
pt	Portuguese	250M	1.51%	tr	Turkish	85M	0.98%	ceb	Cebuano	21M	0.00%
ru	Russian	145M	9.16%	vi	Vietnamese	86M	1.35%	sw	Swahili	16M	0.01%
ja	Japanese	124M	4.72%	ms	Malay	82M	0.03%	km	Khmer	16M	0.02%
pl	Polish	38M	1.69%	mr	Marathi	83M	0.04%	my	Burmese	33M	0.03%
th	Thai	38M	0.64%	te	Telugu	83M	0.03%	uk	Ukrainian	32M	0.60%
jv	Javanese	69M	0.00%	fa	Persian	65M	0.79%	lt	Lithuanian	2.8M	0.18%
it	Italian	63M	2.33%	gu	Gujarati	58M	0.03%	el	Greek	12M	0.69%
bg	Bulgarian	8M	0.32%	sq	Albanian	7.5M	0.05%	af	Afrikaans	7M	0.01%
no	Norwegian	5.3M	0.37%	hr	Croatian	5.1M	0.24%	he	Hebrew	5M	0.27%
fi	Finnish	5M	0.41%	da	Danish	5M	0.36%	sk	Slovak	5M	0.35%
et	Estonian	1.1M	0.14%	lv	Latvian	1.75M	0.10%	is	Icelandic	0.314M	0.04%
ga	Irish	—	0.01%								

A.2 Comparison With Other Work

Table 7 presents a comparison between MUBENCH, INCLUDE [29], and BENCHMAX [14]. INCLUDE collects test questions from regional academic and professional certification exams, with a primary focus on local culture and knowledge. It supports 44 languages; however, the test samples are not aligned across languages and the number of samples per language varies significantly. BENCHMAX encompasses a broader range of task types to assess diverse model capabilities, including instruction following and code generation. Nevertheless, each task includes only a small number of samples. Although BENCHMAX is multilingual, it does not emphasize core multilingual capabilities such as natural language understanding and commonsense reasoning. In contrast, MUBENCH offers more

³https://en.wikipedia.org/wiki/List_of_languages_by_number_of_native_speakers

comprehensive coverage in terms of language diversity, capability assessment, and sample volume. It aligns test samples across all supported languages and preserves fine-grained multilingual versions of each question—covering the instruction, question stem, and answer choices. This design enables high flexibility, facilitating the generation of variants tailored to different evaluation scenarios.

Table 7: Comparison of multilingual LLM benchmarks

Benchmark	Supported Languages	Total Samples	Language Aligned	Variant Generation
MUBENCH	61	3,921,751	✓	✓
INCLUDE	44	197,243	✗	✗
BENCHMAX	17	177,684	✓	✗

A.3 Datasets

MUBENCH focuses on core multilingual capabilities, including natural language understanding, commonsense reasoning, factual recall, knowledge-based question answering, academic and technical reasoning, and truthfulness. Therefore, we extend the most widely used English benchmarks for evaluating these capabilities to the multilingual setting. For each benchmark, we extend its test set to the multilingual setting and sample 50 examples from its training or validation set to serve as few-shot demonstrations.

SNLI and MultiNLI SNLI [8] is a widely used dataset for evaluating natural language inference (NLI), where the task is to determine the logical relationship (entailment, contradiction, or neutral) between a given premise and hypothesis. It contains sentence pairs derived from image captions. MultiNLI [36] extends SNLI by including a broader range of genres, such as fiction, government, and telephone speech, making it a more diverse benchmark for evaluating models’ generalization across different domains in NLI tasks. We use the mismatched validation set as the test set and matched validation set for few-shot demonstrations.

StoryCloze Story Cloze Test [23] is a benchmark for evaluating a model’s ability to understand narrative coherence and commonsense reasoning. Each example consists of a four-sentence story followed by two possible endings, and the task is to choose the more plausible ending. The dataset tests whether models can understand everyday events and make realistic predictions about what happens next in a story.

WinoGrande WinoGrande is a large-scale dataset comprising 44,000 problems, designed to evaluate commonsense reasoning in LLMs. Inspired by the original Winograd Schema Challenge (WSC) [19], WinoGrande addresses limitations of earlier datasets by increasing both the scale and difficulty of the tasks. Each problem presents a sentence with an ambiguous pronoun and two possible antecedents; the task is to determine the correct referent based on commonsense understanding. We use its validation set as the test samples.

MMLU and MMLUPro The MMLU [13] dataset is a benchmark designed to assess language models’ knowledge and reasoning across 57 subjects, including math, history, law, and medicine, using over 15,000 multiple-choice questions with four options each. MMLUPro [35] is an enhanced version that introduces more challenging questions, each with ten answer choices, making the task significantly harder and reducing the likelihood of guessing correctly. It is designed to better evaluate models’ reasoning abilities and robustness across diverse prompts and domains.

ARC ARC [10] is a benchmark designed to evaluate the abilities in advanced question answering. It comprises 7,787 multiple-choice science questions sourced from grade-school exams, divided into two subsets: the Easy Set and the Challenge Set. The Challenge Set includes questions that are difficult for simple retrieval or co-occurrence-based models.

GPQA GPQA [28] comprises 448 multiple-choice questions in biology, physics, and chemistry, crafted by domain experts to assess the reasoning abilities of both humans and LLMs. Designed to be exceptionally challenging.

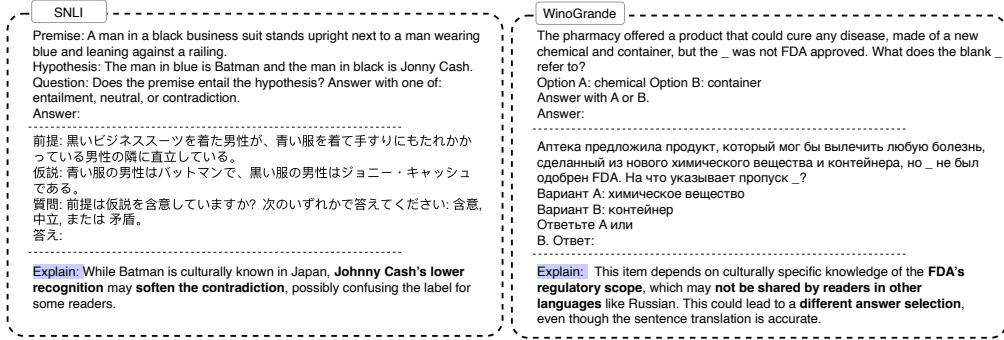


Figure 7: Cultural or background sensitive samples.

TruthfulQA TruthfulQA [21] is a benchmark designed to evaluate the truthfulness of language models in generating answers to diverse questions. The benchmark includes 817 questions covering 38 categories and targets “imitative falsehoods,” which are false answers that resemble common misconceptions found in the models’ training data. The goal is to assess the likelihood of models producing false or deceptive information without task-specific fine-tuning. We expand its validation set as our test set.

BMLAMA BMLAMA [25] is designed to evaluate the cross-lingual consistency of factual knowledge in multilingual LLMs. The test questions in this benchmark are aligned across all languages. We expand the 17-language version, BMLAMA-17, which contains 6,792 samples per language. However, upon inspection, we found numerous issues in BMLAMA-17, including inconsistencies among answer choices across different language versions. Therefore, we re-extended the dataset from its English version to 61 languages. MuBench does not include the original non-English samples from BMLAMA.

HellaSwag HellaSwag [39] is a sentence completion task designed to test commonsense reasoning. Each example provides a short context followed by four possible sentence endings, and the model must choose the most plausible one. The incorrect options are crafted to be grammatically and stylistically similar, making the task challenging and requiring more than just surface-level understanding.

A.4 Cultural Sensitivity

Analyzing the culturally sensitive samples reveals that, although our prompt instructed GPT-4o to flag only cases where cultural differences clearly influence the correct answer, the model adopted a more conservative criterion. It frequently identified content involving religion, region-specific knowledge, and niche cultural references as culturally sensitive. Given that the original datasets were created in English and contain numerous Western—particularly U.S.-centric—cultural assumptions, removing such samples helps mitigate cultural bias and supports a fairer, more balanced evaluation of LLMs across languages. Figure 7 illustrates two examples of culturally sensitive cases.

Table 8 presents a comparison between human experts and GPT-4o in labeling samples for cultural adaptability. Human experts identified significantly fewer culturally sensitive samples than GPT-4o. However, when we separately examine the human annotations for samples that GPT-4o labeled as sensitive and non-sensitive, we find that samples flagged as sensitive by GPT-4o are much more likely to be marked as sensitive by human experts as well.

Case analysis reveals that GPT-4o tends to flag samples involving niche cultural references tied to specific regions, religious topics, or similar themes. More specifically, because these datasets originate in English, they contain a substantial number of samples with a Western-centric perspective. While such content may not directly hinder the ability to answer the original questions, it implicitly assumes that LLMs respond from a Western cultural background. Using such samples to evaluate multilingual models may introduce or amplify regional and cultural biases in the development of LLMs.

Table 8: Per-language Cultural Sensitivity Agreement between GPT and Human Annotators

Language	n	GPT True Count	Human True GPT=True	Human True GPT=False
id	2452	1193	0.023	0.004
de	2155	980	0.042	0.018
ms	2159	958	0.313	0.013
fr	2008	927	0.033	0.026
tr	1893	901	0.069	0.011
ru	1830	856	0.105	0.017
ja	1850	848	0.134	0.046
it	2128	839	0.156	0.061
zh	1849	706	0.540	0.160
es	1745	669	0.027	0.005
th	1917	669	0.039	0.021
nl	1667	653	0.230	0.229
pt	1807	555	0.040	0.013
ko	1762	485	0.165	0.046
vi	1619	450	0.013	0.006
tl	1640	325	0.332	0.077

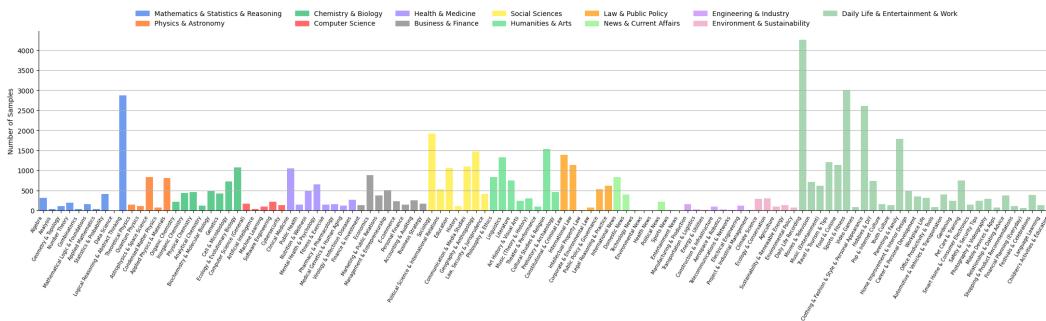


Figure 8: Sample content classification.

As a result, we excluded samples labeled as culturally sensitive by GPT-4o from the final dataset. The impact of these samples on model behavior will be further investigated in future work.

A.5 Diversity

Figure 8 presents the distribution of all MUBENCH samples based on the two-level classification scheme. MUBENCH demonstrates substantial diversity, encompassing a broad spectrum of academic disciplines and everyday topics. Daily life scenarios constitute a significant portion of the dataset, largely contributed by sources such as SNLI, MultiNLI, StoryCloze, and Winogrande. This diversity in real-world content is crucial for assessing the semantic understanding capabilities of LLMs across multiple languages.

A.6 Quality Control

We first extract all samples labeled as culturally sensitive by GPT-4o from SNLI, MNLI, WinoGrande, HellaSwag, BMLAMA, ARCEasy, ARCChallenge, StoryCloze, and MMLU. Then, we perform sampling based on semantic consistency scores and language purity scores estimated by GPT-4o during the translation process, aiming to ensure that there are at least 30 samples for each score level whenever possible. Additionally, we include samples extracted from OpenAI’s MMMLU. All selected samples are then submitted to human experts for evaluation of semantic consistency, purity, and cultural sensitivity, using the same rubrics as those employed by GPT-4o. Notably, when asking human experts to evaluate semantic consistency, we directly provide the original and translated versions without performing back-translation.

Table 9 presents the average scores given by human experts and GPT-4o for each dataset. It can be observed that GPT-4o generally rates the translations more strictly than human evaluators. Across the datasets, the expert scores do not show significant variation, indicating that the translation quality is consistently high regardless of the dataset content.

Table 9: Comparison of Human and GPT Consistency and Purity Scores across Datasets

Dataset	Samples	Semantic Consistency		Translation Purity	
		Human	GPT	Human	GPT
MNLI	3757	4.6577	3.4195	4.5885	3.4482
SNLI	3623	4.6953	3.7248	4.6539	3.8184
ARCEasy	2561	4.8684	4.0016	4.8134	4.3811
ARCChallenge	2161	4.8903	4.1731	4.8066	4.3734
WinoGrande	2643	4.7499	4.0851	4.7662	3.5634
BMLAMA	1499	4.8953	4.3062	4.5264	3.5911
Hellaswag	3668	4.7001	4.2435	4.4959	3.4602
StoryCloze	2389	4.7401	4.3713	4.6756	3.7874
MMLU	8180	4.7605	4.4189	4.6632	3.8302

Figure 9 exhibits the distributions of semantic consistency and purity scores in each language rated by GPT-4o.

B Implementation Details

B.1 Evaluation

All evaluations of open-source models were conducted on a single 8xH100 GPU cluster node. The evaluation code was based on the Hugging Face Transformers⁴ library, and for models larger than 20B parameters, we used vLLM⁵ for inference.

B.2 Parallel Corpora Experiment

Training Data We process Common Crawl snapshots with deduplication and heuristic filtering pipelines inspired by SlimPajama [5] and FineWeb-Edu [24].

Model Architecture We adopt a transformer architecture based on the LLaMA-2 model, scaled to approximately 1.2 billion parameters. All models are initialized randomly prior to pretraining. Table 10 provides the full configuration details and training hyperparameters. To support training, we construct a custom Byte-Pair Encoding (BPE) tokenizer using the BBPE algorithm, resulting in a vocabulary of 250,000 tokens. The primary experiments are run on 64 NVIDIA H100 GPUs, with each experiment taking roughly 50 hours on average.

B.3 Prompt Design

The following contains the prompts used during the construction of MuBench, including the main stages content classification, translation, semantic consistency evaluation, translation purity assessment, and cultural sensitivity check. For semantic consistency evaluation, first the back translation is involved and then the scoring follows.

⁴<https://huggingface.co/docs/transformers>

⁵<https://github.com/vllm-project/vllm>

Model Configuration	Value
Number of attention heads	16
Number of layers	24
Hidden size	2048
Intermediate layer dimension	5504
Maximum position embeddings	4096
Layer normalization epsilon	1×10^{-5}
Training Hyperparameters	Value
Batch size	3072
Sequence length	4096
Optimizer	AdamW
Learning rate	4.3×10^{-4}
Learning rate schedule	Cosine decay to 10% of initial value
Training steps	Varied based on total token budget
Precision	bfloat16 (mixed-precision training)

Table 10: Model configuration and training hyperparameters used for LLM pretraining.

Translation Prompt

Please translate the entire text, into {target language}.

Translate **all content**, including prompt indicators (e.g., Premise, Hypothesis, Question, Choice, Option, Answer, header, title, step, substeps, etc.), partial phrases, and any other English words or phrases. **Do not** leave any part untranslated.

Strictly preserve:

- All original HTML tags (such as <p>, , <s1>, etc.) and their structure
- All special symbols and placeholders, especially underscores _ which indicate missing words or pronouns
- Option labels such as A, B, C, D (used in multiple-choice questions) must remain unchanged
- All line breaks, punctuation, and formatting

The translation must **not** reveal or imply the correct answer. **Do not** modify the wording in a way that would make one choice obviously correct or invalid.

The question must remain **valid, challenging, and unbiased**, as in the original English.

The translation must also be natural, fluent, and contextually appropriate, as if written by a native speaker.

Do not add any explanation, annotation, or commentary.

Text:

{original text}

Back Translation Prompt

Please translate the text back into English.
Strictly preserve all original HTML tags (such as <p></p>), formatting, punctuation, line breaks, and structure.
Do **not** answer any questions or interpret the meaning — just provide a **faithful translation** of the text.
Do **not** add any explanation or commentary.

Text:

{translated text}

Semantic Consistency Scoring Prompt

You will be given two English texts: an original and a rewritten version.
Score the rewritten version's consistency with the original on a scale of 1 to 5, based on these criteria:
5 points: Completely consistent — the rewritten version conveys exactly the same meaning as the original.
4 points: Mostly consistent — only very minor wording changes with no effect on understanding.
3 points: Generally consistent — some differences that might slightly confuse.
2 points: Significant differences — clear changes that can affect the answer.
1 point: Completely inconsistent — the meaning has fundamentally changed.

Original Text:

{original text}

Rewritten Text: {back translated text}

Only output a single digit between 1 and 5.

Cultural Sensitivity Judgment Prompt

Please determine whether the following question contains cultural context or background that would definitively cause the meaning or correct answer to change when translated into {target language}.

Only respond with "Yes" if there is a clear cultural difference that would lead to a different interpretation or answer in the target language. If you are not sure or if no such difference exists, respond with "No". Do not explain your reasoning.

Text:

{original text}

Translated Text:

{translated text}

Category Prompt

Please choose the most relevant category for this text, focusing on the content and scenario described in the question stem or the main body of the text, rather than the question type or answer format.

Categories: {categories}. Only output one of these categories without any explanation, even if the question type might be misleading.

Text:

{text}

Language Purity Scoring Prompt

Evaluate the language purity of the text, based on how fully it is written in {Target Language}.

Give a score from 1 to 5, where:

5 — The text is written entirely in {Target Language}, with **no English words at all**, not even one.

4 — The text is mostly in {Target Language}, but includes a few English loanwords, brand names, or transliterations that are commonly accepted.

3 — The text contains some English words, names, or abbreviations that are not necessary and could have been translated.

2 — The text mixes {Target Language} with many English terms that break the language flow and reduce clarity.

1 — The text contains a large amount of English or appears heavily code-mixed, making it hard to identify {Target Language} as the dominant language.

Ignore option labels such as A, B, C, D — they are not considered part of the language and should not affect the score.

Only reply with a number from 1 to 5. Do not include any explanation or reasoning.

Text to evaluate:

{translated text}

C Full Results

MuBench includes datasets of varying difficulty levels. Some test sets are particularly challenging for base models. Due to space limitations, we only present the results on key datasets in the main text and omit those test sets that are excessively difficult for base models such as MMLUPro and GPQA.

Table 11 presents the full results on all datasets of MUBENCH. Table 12 shows the full results of multilingual consistency on all datasets of MUBENCH.

D Cost Estimation

We used GPT-4o-2024-05-13 for all translations, with a total cost of approximately \$57,038. In addition, using GPT-4o-2024-05-13 for evaluation across all languages incurred a total cost of \$6,441. Evaluating all other open-source models required approximately 8,064 H100 GPU hours. The cost of human expert evaluations was around \$31,212. Annotators were paid at an hourly rate of \$16, with a maximum of 8 working hours per day.

Table 11: Performance of LLMs on MUBENCH. The values in parentheses indicate the score differences relative to English performance.

	SNLI	MultiNLI	StoryCloze	WinoGrande	BMLAMA	MMLU	MMLUPro	HellaSwag	GPTQA	ARCEasy	ARCChallenge	TruthfulQA
<i>Proprietary Model</i>												
gpt-4o-2024-05-13	78.74 (-8.57)	69.78 (-11.18)	97.68 (-1.62)	71.68 (-0.90)	66.87 (-0.35)	70.01 (-2.26)	38.22 (-5.65)	83.02 (-0.75)	30.15 (+2.92)	93.64 (-5.00)	87.32 (-7.35)	75.25 (-6.38)
<i>Model (1-4B)</i>												
Qwen3-0.6B-Base	41.21 (-25.96)	38.45 (-30.53)	56.05 (-15.78)	50.67 (-6.20)	27.17 (-32.19)	26.88 (-5.38)	9.12 (-2.11)	31.01 (-21.29)	22.16 (-0.83)	29.75 (-19.25)	24.62 (-8.89)	28.60 (-2.86)
Qwen3-1.7B-Base	54.36 (-31.13)	56.33 (-24.75)	59.71 (-17.84)	50.99 (-6.30)	31.89 (-28.45)	28.13 (-7.30)	10.41 (-4.46)	35.68 (-28.29)	23.06 (-1.49)	33.46 (-23.00)	26.88 (-9.80)	29.83 (-1.80)
Qwen3-4B-Base	72.06 (-10.42)	69.26 (-4.47)	64.16 (-17.19)	53.27 (-10.04)	37.82 (-26.87)	30.18 (-8.38)	12.81 (-5.82)	42.52 (-29.57)	22.19 (-1.25)	37.55 (-19.51)	30.09 (-9.43)	31.25 (-0.89)
Qwen2.5-0.5B	35.39 (-28.03)	35.10 (-25.94)	54.26 (-17.10)	50.39 (-3.44)	26.42 (-39.25)	26.27 (-4.85)	8.71 (-1.46)	29.42 (-20.54)	21.36 (-0.52)	28.06 (-21.83)	23.67 (-7.34)	25.45 (-4.14)
Sailor2-1B	34.30 (-20.58)	34.56 (+2.06)	54.82 (-18.32)	49.98 (-5.50)	28.37 (-37.95)	26.22 (-3.45)	8.57 (0.11)	29.88 (-20.30)	21.94 (0.06)	28.83 (-18.18)	23.51 (-5.79)	26.04 (-2.36)
Qwen2.5-1.5B	46.19 (-41.99)	46.11 (-29.98)	56.17 (-24.63)	50.48 (-10.94)	31.91 (-37.04)	27.19 (-7.73)	9.34 (-3.36)	31.64 (-33.95)	21.80 (-2.53)	29.51 (-24.67)	24.62 (-12.92)	27.37 (-3.92)
gamma-3-1b-pt	32.89 (-0.75)	32.66 (+0.22)	56.91 (-10.74)	51.62 (-5.76)	41.71 (-27.31)	26.62 (-1.29)	10.36 (-0.71)	31.11 (-13.02)	22.41 (-1.25)	28.94 (-7.77)	24.84 (-2.05)	29.83 (-0.78)
gamma-3-4b-pt	43.20 (-15.41)	42.48 (-5.82)	58.31 (-9.65)	56.01 (-11.43)	52.57 (-17.96)	26.70 (-1.40)	9.99 (-0.37)	34.31 (-16.81)	22.63 (-2.15)	29.26 (-10.08)	24.47 (-2.94)	27.35 (+0.31)
gamma-2-2b	36.43 (+0.63)	34.51 (-12.74)	63.98 (-18.91)	52.53 (-11.94)	40.48 (-30.73)	28.05 (-6.27)	11.27 (-4.30)	40.29 (-30.46)	22.42 (-1.46)	33.45 (-16.53)	27.36 (-8.81)	30.74 (-0.89)
<i>Model (7-20B)</i>												
Qwen3-8B-Base	80.12 (-6.73)	76.16 (-6.56)	67.87 (-16.42)	55.41 (-12.03)	47.44 (-24.70)	31.47 (-8.14)	14.09 (-6.00)	47.72 (-28.02)	24.30 (-2.49)	40.51 (-17.90)	31.73 (-8.13)	32.42 (-0.23)
Qwen3-1.4B-Base	84.20 (-3.59)	81.63 (-0.92)	71.14 (-13.61)	57.67 (-15.04)	51.72 (-21.14)	32.61 (-8.22)	15.74 (-6.15)	52.86 (-25.90)	26.08 (-2.04)	42.75 (-15.41)	33.71 (-5.98)	33.54 (-2.68)
Qwen2.5-7B	68.28 (-21.13)	67.23 (-18.14)	61.88 (-22.02)	51.08 (-14.68)	36.02 (-36.86)	29.77 (-9.56)	11.76 (-5.27)	39.52 (-36.92)	22.91 (-1.87)	35.49 (-24.49)	28.14 (-11.98)	28.96 (-4.88)
Sailor2-8B	52.8 (-27.29)	54.66 (-25.99)	61.89 (-20.62)	52.59 (-11.96)	40.26 (-30.47)	28.25 (-7.76)	10.09 (-3.81)	38.44 (-34.76)	22.77 (-0.22)	34.11 (-22.44)	26.62 (-11.01)	27.56 (-1.52)
Babel1B	68.26 (-21.89)	66.38 (-22.27)	61.96 (-21.48)	53.29 (-14.72)	42.73 (-29.34)	29.15 (-9.30)	11.76 (-5.34)	40.57 (-34.25)	22.77 (-1.04)	34.25 (-27.73)	27.64 (-13.08)	28.26 (-1.84)
Qwen2.5-14B	76.04 (-1.095)	74.24 (-11.83)	66.50 (-19.26)	50.19 (-11.89)	23.68 (-31.04)	31.64 (-9.70)	13.92 (-5.82)	45.62 (-35.09)	24.03 (-1.19)	39.05 (-20.59)	31.13 (-0.84)	31.13 (-0.84)
Sailor2-20B	75.26 (-15.83)	73.36 (-16.07)	67.41 (-18.50)	56.30 (-18.64)	48.11 (-25.13)	30.61 (-8.94)	12.71 (-5.62)	46.74 (-32.83)	24.10 (-0.22)	38.14 (-20.95)	30.36 (-1.07)	30.02 (-4.33)
gamma-3-12b-pt	51.85 (-15.21)	37.08 (-4.45)	55.42 (-4.02)	61.40 (-11.56)	59.61 (-12.17)	26.27 (-0.87)	10.13 (-0.67)	30.50 (-4.01)	23.26 (+0.05)	28.27 (-3.40)	24.23 (+1.21)	26.22 (-0.82)
gamma-2-9b	69.92 (-5.87)	65.10 (-12.05)	73.40 (-12.28)	57.98 (-13.83)	53.59 (-18.12)	31.64 (-7.18)	14.87 (-4.44)	55.66 (-22.19)	24.20 (-1.92)	41.75 (-13.91)	33.27 (-7.11)	32.25 (+0.28)
<i>Model (>20B)</i>												
Qwen2.5-32B	81.67 (-9.51)	80.36 (-7.61)	68.19 (-18.57)	56.95 (-17.91)	48.84 (-23.45)	33.30 (-8.51)	16.09 (-5.47)	49.43 (-32.07)	24.15 (-3.53)	41.51 (-17.96)	33.12 (-10.95)	31.85 (-3.69)
Qwen2.5-72B	84.63 (-6.63)	84.48 (-5.53)	71.89 (-15.42)	59.17 (-18.82)	52.87 (-19.79)	36.25 (-7.59)	18.56 (-4.57)	54.99 (-28.77)	25.86 (-1.15)	46.73 (-15.50)	36.40 (-9.13)	34.53 (-3.23)
Babel83B	85.68 (-5.86)	85.29 (-5.04)	71.40 (-15.83)	58.52 (-18.89)	52.46 (-20.91)	34.75 (-8.19)	17.52 (5.06)	54.65 (-28.33)	26.06 (-2.06)	43.98 (-18.51)	34.47 (8.06)	32.88 (-4.36)
gamma-3-27b-pt	81.71 (-5.27)	77.12 (-8.60)	79.06 (-8.48)	63.49 (-13.34)	61.74 (-10.48)	36.46 (-4.84)	19.19 (-4.16)	66.09 (-14.28)	27.35 (-1.47)	48.18 (-7.01)	37.99 (-3.59)	32.19 (-0.46)
gamma-2-27b	79.28 (-8.92)	75.38 (-8.58)	77.21 (-10.17)	60.78 (-15.81)	56.09 (-14.85)	34.09 (-6.76)	17.41 (-4.23)	62.08 (-20.02)	26.40 (-1.72)	44.23 (-9.48)	35.70 (-3.90)	32.40 (-2.46)

Table 12: Consistency across languages. ‘All’ refers to the average consistency across all language pairs, while ‘vs. EN’ indicates the average consistency between each language and English.

		SNLI		MultiNLI		StoryClove		WinoGrande		BMLAMA		MMLU		MMLUPro		HellaSwag		GPOA		ARCEasy		ARCChallenge		TruthfulQA		
		All	vs. EN	All	vs. EN	All	vs. EN	All	vs. EN	All	vs. EN	All	vs. EN	All	vs. EN	All	vs. EN	All	vs. EN	All	vs. EN	All	vs. EN	All	vs. EN	
Proprietary Model		78.37	83.63	74.60	79.25	96.71	98.06	74.93	78.54	66.21	74.67	68.42	69.71	42.46	47.07	83.37	86.95	47.46	43.93	90.34	94.28	84.52	89.24	80.62	83.63	
Model (1-4B)		42.32	48.53	49.51	51.04	64.15	62.68	55.10	57.79	29.64	35.36	49.22	48.98	44.84	42.07	49.68	45.60	64.00	63.52	39.42	40.44	40.94	41.26	55.71	51.53	
Owen3-0.6B-Base		53.28	61.02	56.72	62.92	65.67	67.12	55.84	54.96	33.92	42.06	49.82	50.21	44.14	42.48	50.91	48.79	64.00	64.70	41.45	43.91	42.66	43.48	56.39	54.98	
Owen3-1.7B-Base		75.54	70.39	70.99	67.89	69.64	57.28	60.18	54.11	36.24	44.74	51.08	52.36	44.42	43.41	53.48	54.04	64.16	65.36	43.54	46.92	44.13	45.65	56.40	54.87	
Owen3-3.4B-Base		41.39	32.35	42.98	48.39	62.45	60.86	54.09	54.11	34.21	47.67	45.94	45.06	40.15	47.63	42.30	62.83	60.68	37.17	39.40	38.03	38.03	54.06	51.49		
Owen3-5.0B		49.24	15.33	58.48	71.72	62.71	61.63	54.75	55.64	28.96	48.64	48.28	46.54	43.36	47.89	43.45	63.88	62.98	38.56	39.51	40.45	40.46	53.76	52.19		
Sailor2-1B		43.09	52.32	45.29	55.07	63.38	62.97	54.18	55.19	32.64	40.60	48.31	47.52	43.53	39.96	48.21	43.50	63.44	61.53	38.57	39.92	39.87	38.64	54.14	51.67	
Owen2-5.1B		42.90	44.96	86.21	92.38	65.71	66.21	55.84	58.85	40.64	51.17	52.79	54.52	48.13	48.67	50.64	50.74	65.85	67.30	40.81	43.46	42.78	43.76	52.52	53.49	
gemini-3.1B-pt		43.49	48.92	48.92	42.04	44.77	66.11	66.30	59.46	62.38	51.35	61.04	50.89	53.02	45.52	45.80	51.50	51.40	64.08	64.18	39.47	42.46	41.23	42.81	51.49	52.83
gemini-3.4B-pt		35.45	43.90	41.50	29.26	67.46	70.27	55.75	58.26	39.24	49.81	53.82	54.36	48.60	47.53	51.53	52.15	67.84	68.35	43.21	46.23	44.09	45.98	56.68	56.45	
Model (7-20B)		78.37	81.58	74.47	78.24	69.90	72.52	58.79	62.14	45.48	55.63	51.39	52.52	44.59	43.79	56.02	58.20	64.79	66.12	45.23	48.91	45.21	46.85	57.40	56.00	
Owen3-8B-Base		83.45	83.85	80.76	79.75	72.01	74.85	60.12	63.72	59.66	54.06	45.02	44.74	58.75	52.59	64.85	66.84	46.26	46.01	48.45	48.45	58.61	58.76			
Owen3-14B-Base		65.59	74.58	65.37	74.53	66.10	68.76	54.96	56.65	34.49	42.58	49.28	50.29	42.92	42.04	50.72	51.05	61.89	62.62	41.29	45.31	41.33	43.29	55.19	54.90	
Owen2-5.7B		53.75	62.30	49.86	60.37	66.55	68.44	56.51	58.37	38.36	48.17	50.40	50.93	44.98	43.13	51.13	50.40	64.89	64.63	42.04	44.87	42.07	43.57	54.14	53.91	
Sailor2-8B		62.61	72.29	58.75	69.49	65.08	68.86	57.03	59.66	40.97	51.46	46.99	49.04	40.81	40.83	50.50	52.44	61.82	63.79	39.53	44.21	39.66	42.06	47.47	50.70	
Babel-9B		74.94	80.05	74.97	79.11	68.59	72.11	57.45	56.17	26.19	31.21	50.08	51.71	43.35	42.79	53.83	56.40	62.96	64.29	43.20	47.79	42.89	45.41	56.55	55.89	
Owen2-5.14B		75.07	80.40	70.00	74.91	73.61	77.25	60.18	64.31	51.62	61.12	55.87	57.51	50.12	49.77	60.41	64.38	71.00	73.30	47.12	51.71	47.02	49.58	57.85	57.82	
Model (>20B)		81.18	85.94	80.83	84.48	69.48	72.74	58.74	61.98	46.54	56.12	50.91	52.75	43.07	43.12	55.57	59.19	61.88	63.80	44.21	48.69	43.74	47.11	57.01	56.19	
Owen2-5.32B		84.69	88.64	84.65	88.06	71.89	75.87	60.01	64.32	50.23	59.90	53.01	55.39	45.08	45.26	59.12	63.65	64.67	66.63	47.44	52.25	45.83	49.05	58.07	59.10	
Babel-8.32B		86.30	89.37	85.20	88.34	71.83	75.46	60.00	64.44	50.17	59.73	52.70	55.09	45.46	45.64	59.17	63.59	65.66	66.39	46.24	50.90	45.59	48.59	55.89	57.83	
gamma-3-27b-pt		82.68	86.53	77.43	82.09	78.16	81.36	64.50	69.68	61.02	68.10	58.66	61.91	53.24	54.88	68.55	72.63	73.72	74.46	52.16	55.87	51.07	54.29	60.85	61.94	
gamma-2-27b		79.14	82.88	74.24	77.78	76.15	79.80	61.57	65.91	53.65	62.81	55.39	58.03	47.98	48.62	64.55	69.50	66.33	68.82	48.27	51.44	48.06	51.77	59.25	61.73	



Figure 9: Consistency and purity distributions evaluated by GPT-4o (Part 1/6)



Figure 9: Consistency and purity distributions evaluated by GPT-4o (Part 2/6)

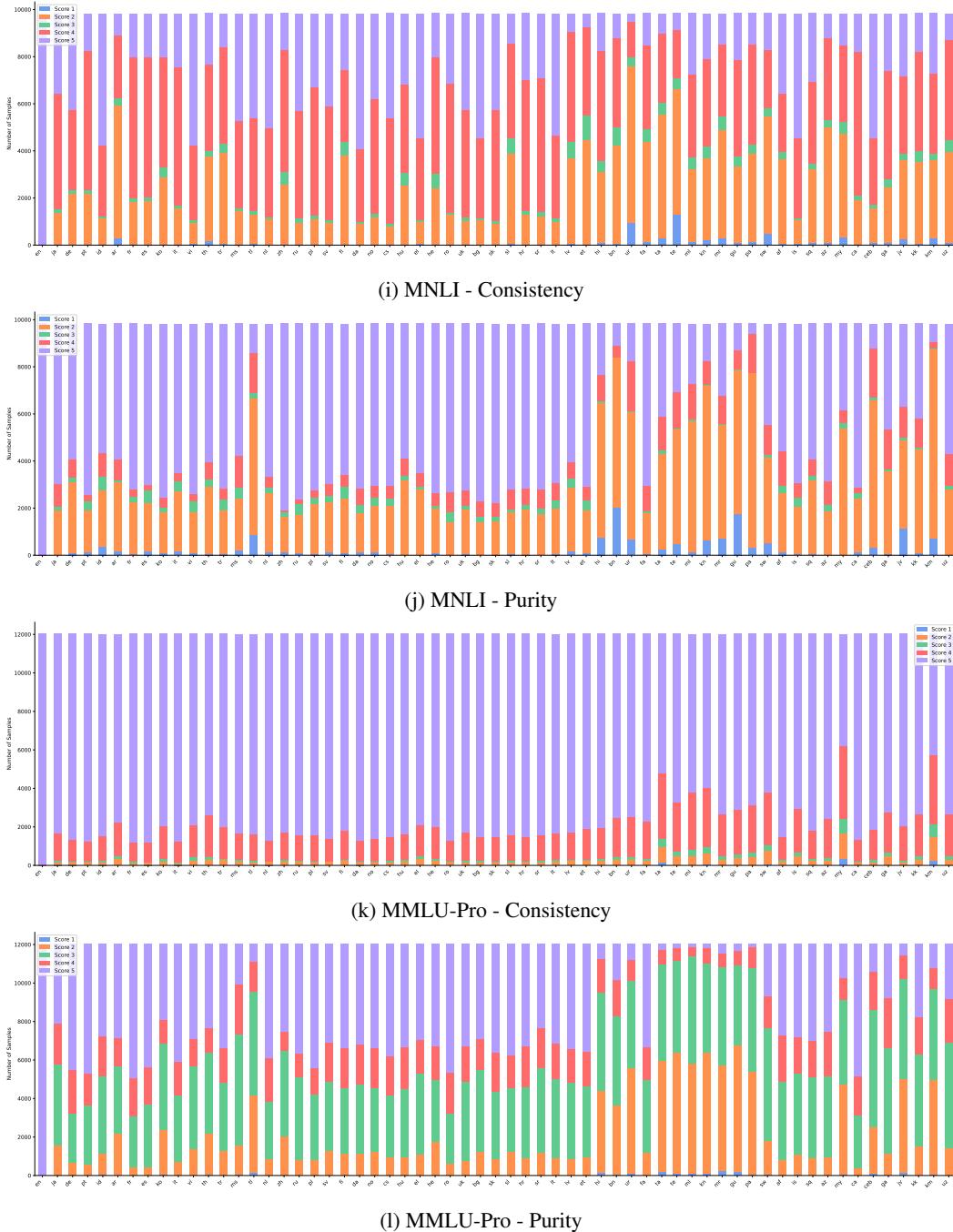


Figure 9: Consistency and purity distributions evaluated by GPT-4o (Part 3/6)

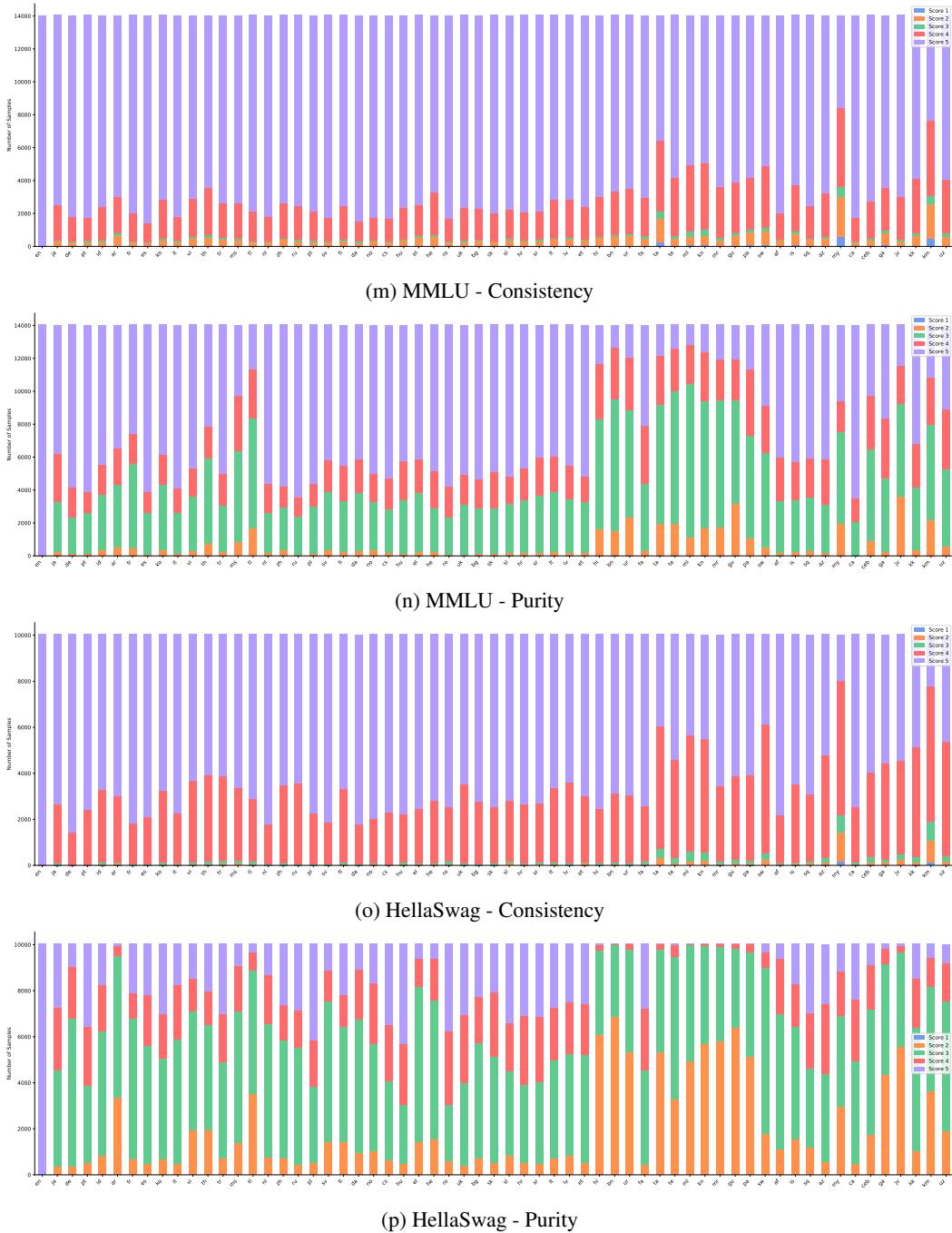


Figure 9: Consistency and purity distributions evaluated by GPT-4o (Part 4/6)



Figure 9: Consistency and purity distributions evaluated by GPT-4o (Part 5/6)



Figure 9: Consistency and purity distributions evaluated by GPT-4o (Part 6/6)